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ELECTRICITY, CARBON AND WEATHER IN FRANCE
WHERE DO WE STAND ?

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Abstract: As a tool to fight long run changes in climate the European Union explicitly introduced the emission trading scheme (EU ETS) on January 1, 2005, which aimed at reducing carbon emission by 8% by 2012, and was designed to operate in two phases. Using data related to the first phase, this article investigates the role that the EU ETS plays in the power generation market by taking into account the existence of possible cross-spillovers between the French carbon and the French electricity spot markets, the spot prices of natural gas and of oil, and climatic conditions in France and elsewhere. Results show that there is no short run relationship between the electricity and carbon returns, while there is a long run relationship.
However, this relationship suffers from a disequilibrium in that the electricity price readjust in the long run. We also find that while there are own mean and own volatility spillovers in the two markets, there are no cross own mean and own volatility spillovers, indicating that the electricity spot market and the carbon spot market are not integrated. Finally, results underline the limited impact of weather on the interconnection of these markets.

Key Words : Carbon market, Electricity, Weather, Multivariate GARCH

Classification JEL: C3, G1, Q4, Q5

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1 Introduction

Climate change is arguably the greatest environmental challenge that the world faces today. In its latest assessment report the IPCC (2007) underlines the considerable progress that has been made in understanding how climate is changing in space and in time. More specifically, it concludes that *"warming of the climate system is unequivocal, as is now evident from observations of increases in global average air and ocean temperature, widespread melting of snow and ice and rising global average sea level"*. It also points out that, although climate has always been changing, the likelihood of a human contribution to the current evolution and observed trend is *"more likely than not"*. Projections of future changes in climate emphasize, for the next two decades, a warming of about 0.21°C per decade, and *"even if the concentration of all greenhouse gases had been kept constant at year 2000 level, a further warming of about 0.11C per decade would be expected"*(IPCC, 2007).

As a tool to fight such changes in climate the European Union explicitly introduced the emission trading scheme (EU ETS) on January 1, 2005, which aimed at reducing carbon emission by 8% by 2012. More specifically, it set caps for CO2 emissions for some 11,500 plants across the EU-25, where, as noted by Reinaud (2007), installations have the flexibility to increase emissions above their cap through the acquisition of emission allowances and the sale of unused ones. In this regard, it is designed to operate in two phases, the first from 2005 to 2007, while the second spans the period 2008 to 2012. Each of these phases corresponds to a National Allocation Plan (NAP) which specifies the total number of emissions allowances allocated (free of charge) to the individual installations covered by the scheme. Transactions of such allocated allowances are then made possible through a an EU allowances (EUA) market (spot market) that provides a visible price of CO2.

Importantly, as noted by the World Bank (2007), the first phase of the EU ETS can be viewed as a *"pratical experiment to manage GHGs emissions"* (World Bank (2007), p16). Thus researchers are now, at the start of the second phase, presented with the prime opportunity of evaluating the role that such a emission trading platform plays in the power generation market. As a matter of fact, only a year after the launch of the EU ETS, there had already been clear signs of its success. For instance, the World Bank's latest report emphasizes that, among all the "cap-and-trades" regimes in the world (i.e., EU ETS, New South Wales, Chicago Climate Exchange, UK ETS), the EU ETS is *"the largest carbon market by far"* that combines environmental performance and flexibility through trading (World Bank (2007), p11). For instance, the Caisse des Depots[1] recorded 817, 9 Mt of CO2 at a total value of EUR 14, 6 billion of annual transaction in 2006

[1]The Caisse des Dépôts is a public financial institution that performs public-interest on behalf of the French central, regional and local governments. It is also the French national greenhouse gas registry.

(this represents an increase of 197% compared to 2005). However, the considerable volatility of the observed price of carbon has also raised some concern. For example, in the first few months of 2005 carbon allowances were traded at about EUR 7/tonne, rising to EUR 29/tonne in July, and then falling to EUR 20/tonne a month later. By April 2006, daily prices had again risen to over EUR 30/tonne, but fell to below EUR 10/tonne at the end of the month. Such rather severe movements of the carbon price indicate a basic uncertainty in the underlying annual price of abatement. In particular, the Caisse des Depots points out that far less abatement had been needed in the first year than expected[2]. Moreover, a World Bank survey (2007) indicates that the inability to bank unused allowances had also influenced the level of the carbon price.

Perrels, Malkönen and Honkatukia (2006) argue that the basic effect of the introduction of a market such as the EUA on the cost of electricity (and thus on the wholesale and spot prices) is quite straightforward: the cost of CO2 will exert a pressure on generators to increase prices at the margin. As a matter of fact, Perrels et al. (2006) note that such a pass through of carbon prices into product prices (electricity and energy materials) has already been highlighted by various empirical studies (Damailly and Quirion, 2006; Smale et al., 2006; Fezzi, 2006). For example, Sijm et al. (2006) study the impact of free allowances of CO2 emissions on the price of electricity. The authors note that for a power company emissions allowances are considered as an opportunity cost that should be added to all the other marginal costs of the company. Using empirical estimations for Germany and the Netherlands they show that power producers indeed pass this opportunity cost to the price of electricity, and that the rate of such a pass-through varies from 60 to 100%, where its (and thus the increase in electricity prices) mostly depends on the power mix of the country. Hauch (2003), in contrast, uses a general equilibrium model to study the consequences of reaching the emission reduction target in the Nordic electricity market, in particular how it affects the cost of electricity, over the period 1995 to 2020. The author defines marginal CO2-abatement curves in Denmark, Sweden, Norway and Findland, for the year 1995, either when international electricity and/or emission permits trading is possible or not. He finds that, to reduce emissions by 20%, the marginal cost should be equal to EUR 45/tCO2 when there is no possibility of trading, EUR 39/tCO2 when free permits trading is possible, and EUR 23/tCO2 when both electricity and carbon trades are allowed. Moreover, when emissions trading is possible, the paper estimates the evolution of the equilibrium price of permits: from EUR 60/t in 2010, it raises to EUR 100/t in 2020. Also, using simulations The Energy Business Group[3] found an increase of EUR 7MWh of the equilibrium price on several electricity markets (Germany, Scandinavia, Spain and UK) due to the EU ETS, while OCDE/IAE (2007) noticed that the fall by EUR 10/tCO2 in May 2006 was immediatly followed by a drop in wholesale electricity prices of between EUR $5 - 10$/MWh. However, all of these studies underline that it still remain diffi-

[2]see Tendance Carbone, n°13, April 2007

[3]see Energy Business Group Report (2004)

cult to assess the actual impact of such a new market since several electricity markets across EU, as well as the price of commodities (i.e., natural gas, coal and oil), interact with the UE ETS prices.

Climate variability may also influence the relationship between electricity and carbon prices. More precisely, rainfall impacts the electricity production of a country with regard to its energy mix, and thus influences CO2 emissions. For example, the Spanish electricity market suffered from the low level of rain in winter 2005 and had to replace the shortage in hydro-electric power by thermal and fuel energy. Additionally, temperature may affect the demand side of the electricity market. As recently noticed in France, a drop of 1 degree Celcius of the temperature in winter increase to the need of electricity (CDC, 2006) by $15,000$ MW. However, while there are a few studies (e.g., Energy Business Group, 2004; CDC, 2006) that investigate the relationship between temperature and electricity trading or between rainfall and the carbon market, we are aware of only one that examines the impact of weather on both markets. More specifically, Considine (2000) undertakes an econometric analysis of the energy demand in the US and shows that warmer conditions reduce both energy and demand for CO2 emissions in general. But, importantly, both electricity and carbon emissions allowances are traded on financial markets (forward, futures and spot markets), so that if there is indeed a link between the electricity sector's activity, its emissions, and weather, it has of yet to be explicitly quantified how such links simultaneously affect both organized markets (i.e., electricity spot and/or futures markets and the EUA market).

As it becomes clear, while there are now a growing number of studies relevant to the study of the interaction between carbon and electricity market, there is a clear lack of a comprehensive analysis of the simultaneous interaction between the price of carbon and the price of electricity. In this paper we address this shortcoming by focusing on the French spot market of electricity and carbon emissions allowances trades. More specifically, we explicitly take into acount the existence of possible cross-spillovers between the French carbon market, the French electricity spot market (Powernext Day-Ahead), the spot markets of natural gas and of oil, in regards to climatic conditions in France and elsewhere. In this regard we avail of daily data of the electricty market, both prior to and after the creation of the EUA market, daily carbon price data since the creation of the EUA market, daily price data set on US Henry Hub, daily price data of European Brent, and daily weather (rainfall and temperature) in France as well as other relevant European countries that depend heavily on the French power generation. Our results show that there is no short run relationship between the electricity and the carbon returns, while there is a long run relationship between them. However, this relationship suffers from a desiquilibrium in that the electricity price readjust in the long run. In others words, we show that electrcity returns respond to carbon in the long run, but when taking the impact of weather on this relation into account, the converse seems also to be possible. We also find that while there are own mean and own volatility spillovers on the two markets, there are no cross own mean and own volatility spillovers, indicating that the electricity spot market and the carbon spot market are not integrated. Finally, our results underline the limited impact of weather on the interconnection between these markets.

The remainder of the paper is organised as follows. Section 2 provides an overview of the development and the characteristics of the French emissions trading platform. Section 3 describes the data used in the paper. In Section 4 we outline our empirical model and presents the main results. Finally, Section 5 concludes.

2 History and facts of the EU carbon market and key features on the French trading platform

The first major cross-national step in fighting climate change was made in 1988 by governments with the creation of the Intergovernmental Panel on Climate Change (IPCC), intended to generate a greater understanding of the nature and potential impact of the problem. In it is first report, written in 1990, the IPCC confirmed that climate change was indeed a reality and recommended that countries should take action in the form of an international treaty. In this regard, the Kyoto protocol, which defined mandatory targets for the world's leading economies, was subsequently signed in 1997 by 38 industrialized countries agreeing to reduce their 1990 levels of emissions of greenhouse gases by a total of 5% between 2008 and 2012 (World Bank, 2007) and became effective in 2005. As a tool to drive the implementation of the Kyoto Protocol and to regulate industrial CO2 emissions in the EU bloc, the European Union established the EU Emissions Trading Scheme (EU ETS) in 1995. This scheme regulated in its first phase 40% of EU emissions, and was originally defined for large energy-using installations, namely energy production, metals, construction materials, and paper[4].

The World Bank survey (World Bank, 2007) has emphasized the efficiency of Phase 1 of the EU ETS in reducing GHGs emissions. As a matter of fact, in 2005 they were more than 3% below what had been allocated to countries that year, and data on 2006 emissions reinforce such a trend. Indeed, The Caisse des Dépôts noticed in 2006 an excess of 30Mt of CO2, which represents 1.45% of the initial allowances. As in 2005, the whole market was long[5], and the countries with an excess of allowances were also the same[6]: Poland (+28Mt), France (+22Mt), Czech Republic (+13 Mt), Netherland (+10Mt). Six countries were short[7]: Denmark (66Mt), Slovenia (60,2Mt), Ireland (-3Mt), Spain (-14Mt), Ialy (-26Mt) and UK (-46Mt). However, regarding the different industrial sectors, only the power and heat sector registered, as in 2005, a shortfall. In 2007, such a trend

[4]The power and heat sector received 56% of all the allowances, the minerals and metal sectors received together 35% of them and finally, oil and gas industries got 13% of them.

[5]A market is long when there is an excess of allowances compared to the verified emissions of CO2

[6]see Tendance Carbone, n°6, July 2006

[7]see Tendance Carbone, n°6, July 2006

seems to be reinforced, although one should wait for the publication of the compliance data (i.e., the verified level of emissions in 2007) in May 2008 to confirm this.

Since April 2006, the EUA market has shifted out of Phase 1 into Phase 2 allowances. Trading of emissions allowances of the first phase closed on March, 30th, while those for Phase 2 had already begun through futures contracts on the ECX platform prior this date. In May 2006, the volume of such allowances accounted for about 20% of total volumes traded, while the price of the tonne of CO2 was higher than during the first phase. The Caisse des Dépôts underlines that a tonne of CO2 is sold at 22 euros for a delivery later than January 2008. With regard to the experience of Phase 1, the annual cap for the second phase of the scheme is tighter and set at 5,8% below 2005 verified emissions. Moreover, to ensure continuity of the EU ETS, and to improve emissions abatement by installations, banking of unused allowances is now allowed. Several other trends of this scheme are likely to be observed in the future. In particular, the introduction of the aviation sector should largely enhance the reduction of emissions up to 183 MtCO2 per year (World Bank, 2007).

It is noteworthy that during Phase 1 emissions allowances could be trading among several markets in Europe - Powernext Carbon in France, EEX in Germany, ECX in Amsterdam and Londres, Nordpool in Norway and EXAA in Austria - through spot contracts, futures contracts or Over the Counter. In France, for example, Powernext Carbon was launched by Powernext in partnership with Euronext and the Caisse des Dépôts, and offers spot contracts to trade emissions permits by tonnes of CO2 expressed in euros. Delivery of allowances can be made all over EU-25. Permits can be traded continously, five days a week, from 9.00 am to 5.00 pm. In January 2005, Powernext[8] registered 33 active members on Powernext Carbon (banks, market intermediares and energy providers), while this number increased to 49 by 2006. In 2005, the French trading platform shared 59% of all the European organised market. In 2006, transaction volumes on the market represented more than 65% of all the exchange in Europe. 31, 448 000 t of CO2 were traded on Powernext Carbon, which is more than 125,000t a day[9]. Powernext also underlines that average volume quadrupled between 2005 and 2006, whit high transactions volumes in May 2006 when the European Commission published the 2005 compliance data.

In order to implement Phase 2 of the EU ETS, in January 2008 Bluenext was launched by Euronext and the Caisse des Dépôts as a "world market of environmental assets", and is now in charge of the French carbon market platform. As Powernext Carbon, it proposes spot contracts related to the allowances defined by the NAP of the phase 2 (EUA2), but also aims at developing a futures market. Moreover, since carbon transactions can also be done through "project-based

[8] see 2005 and 2006 Powernext activity assessment

[9] see Powernext 2006 activity assessment

transactions"[10], in which the buyer purchases emissions credits (CER) for a project that can demonstrate GHG emissions reductions, derivatives products with underlying CER should also soon be available on Bluenext. With 74 European members, this new market stands as the main successor to Powernext Carbon to carry Phase 2 of the EUA market.

3 Data

3.1 Electricity and carbon spot prices data

Launched in 2001, Powernext is France's first power exchange that proposes financial products to energy providers to manage price risks and volume risks. On Powernext Day-Ahead, participants can trade, from the day before until one hour before delivery, contracts that commit them to inject into or withdraw from the French transmission network a volume of electricity throughout a given hour (or a block of hours), at market price. Then, the contracted electricity can be delivered at any point within the French transmission network. The underlying factor of the financial contracts proposed on such a market is the electricity traded on day d for delivery on the same day or on the following day on 24 individual hours. On Powernext Day-Ahead Auction contracts are auction traded, where the auction is at 11.00 a.m. CET, seven days a week, while on Powernext Day-Ahead Continuous and Intraday, contracts are traded continuously. In this study, we use data regarding Powernext Day-Ahead Auction, which allows us to concentrate orders for each hourly period, and gives us the definition of a unique price for every hour of the following day. Our dataset of this market gathers hourly spot prices (on 24 hours) from 26/11/2001 to 28/12/2007. On each day, a weighted average is also available which is the price series that we use for our empirical analysis.

Across Europe EU alowances are traded among several plateforms or markets. In France, from 2005 to 2007, allowances were traded on Powernext Carbon. This is a spot market on which CO2 permits are continuously traded five days a week, from 9.00 a.m. to 5.00 p.m. Our dataset on this market gathers closing prices from 24/06/05 to 28/12/07.

3.2 Climatic data

Regarding climate data, we use daily rain data in France ($nrain_f$) from 01/01/1990 to 07/11/2006. These data, provided by Meteo France, cover five towns (Paris, Strasbourg, Lyon, Bordeaux and Marseille) that should represent the different parts of the country. Temperature indices, provided by Nextweather, are also available for several European countries: France (from 01/01/1976 to 31/07/06), UK (from 01/01/1996 to 31/07/06), Germany (from 01/01/1996 to 31/07/06), Switzerland (from 01/01/1994 to 31/07/06), Belgium (from 01/01/1994 to 31/07/06), Italy (from

[10]see World Bank (2007) for more details on such projects

01/01/1994 to 31/07/06), Netherlands (from 01/01/1994 to 31/07/06), Spain (from 01/01/1994 to 31/07/06) and Portugal (from 01/01/1994 to 31/07/06). These indices are defined as follows. For each country, Meteo-France calculates the average of the temperatures at the representative regional weather station weighted by the regional population. This demographic information represents a fair approximation of the weight of the regional economic activity. Thus, these indices represent a quality reference allowing one to anticipate and to describe local and geographical more wider meteorological changes. Note that following Pardo, Menue, Valo (2002), we choose to model temperature as a deviation from 18 degrees celcius. Thus, HDD_i, will represent the variations of temperature above 18 degrees celcius in the country i (i.e., $HDD_i = T_i - 18$) and CDD_i the deviations below 18 degrees celcius (i.e., $CDD_i = 18 - T_i$).

3.3 Others commodities data

Regarding others commodities variables that could interact with both the prices of electricity and carbon, we choose to work on data with oil and natural gas. More precisely, for oil, we use daily spot prices of European Brent Crude, one of the major classifications of such kind of fuel. Moreover, oil production from Europe, Africa and the Middle East flowing West tends to be priced relative to this oil. Brent blend is a light crude oil mainly used to produce gasoline, and was originally traded on the open-outcry International Petroleum Exchange in London, but since 2005 has been traded on the electronic IntercontinentalExchange (ICE). Spot prices set on brent are denominated in US/barrel. Our sample covers the period from 20/05/87 to 29/01/08. However, as European daily data on spot prices for natural gas (Zeebrugge hub) were not available before 2006, we decide to use spot prices relative to the the US gas hub; Henry Hub. It is the pricing point for natural gas contract traded on the New York Mercantile Exchange. Spot prices set at Henry Hub are denominated in USD/mmbtu (millions of British Thermal Units). Our sample covers period from 01/11/1993 to 29/01/2008.

3.4 Summary statistics

Overall, as our analysis is conditionned by the availability of both weather and carbon data, the sample under study covers period from 24/06/05 to 31/07/06.

In Figure 1 we depict the evolution of the carbon and electricity prices over our sample period. Examining the first phase of the EUA market, several comments can be made with regard to the volatility of the price of carbon. From January until July 2005, the market became increasingly more operational, although with only a limited number of actors. While the large energy providers were already trading, the others sectors were not ready to enter into the market. Then, from August 2005 to March 2006, the market grew substantially. The price of carbon reached an equilibrium level around EUR 25/t, that resulted from an increase of both the price of natural gas

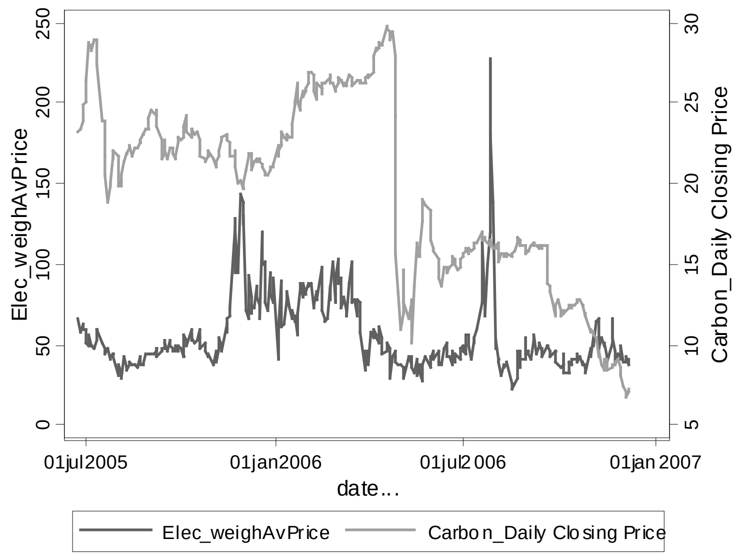

Figure 1: Powernext Day-Ahead price and Powernext Carbon price

during winter, and the demand of allowances in the electricity sector. In February 2006, the spot price was equal to EUR 26,19, which was the highest monthly average, and continued increasing up to EUR 29,43 on April 24th. Such a trend can be explained by a limited decrease in the spread between gas and coal prices, which was not enough compared to the price of carbon to incite electricity providers not to resort to coal. Moreover, the negotiations which took place during these months on the allocated allowances regarding the phase 2 of the market also limited the offer on the carbon marlet (i.e., the industrials with an excess of allowances preferred to keep them).

In May 2006 the price of carbon fell from its highest level to EUR 13,19. This huge drop (i.e., around 65%) is mainly due to the announcement on May 15th of the compliance data for 2005, and the global long position taken by several countries. More precisely, starting from this date, all the actors on the EUA market had the same information concerning the level of emissions in 2005 in the different countries, sectors, and installations, which explain the increase of 51% of the spot price (it reached EURO 16,47 in June 2006). This *"krach test"*[11] underlines the negative effects of a scheme which does not allow actors to keep their unused allowances between the two phases of the market, and thus prevents any possibility of arbitrage. Another unexpected shock

[11] see Tendance Carbone, n°3, May 2006

hit the market in September 2006, where from the 19th to the 26th, the spot price fell down to EUR 12 due to the instability of the commodities market. Indeed, in the preceding month there was a reversal in oil and natural gas prices, which decreased below USD 60/barrel for oil and 52,5 pence/therm for gas prices set at Zeebrugge hub and below USD 5/mmbtu for prices set on the NYMEX-Henry hub (see figure below).

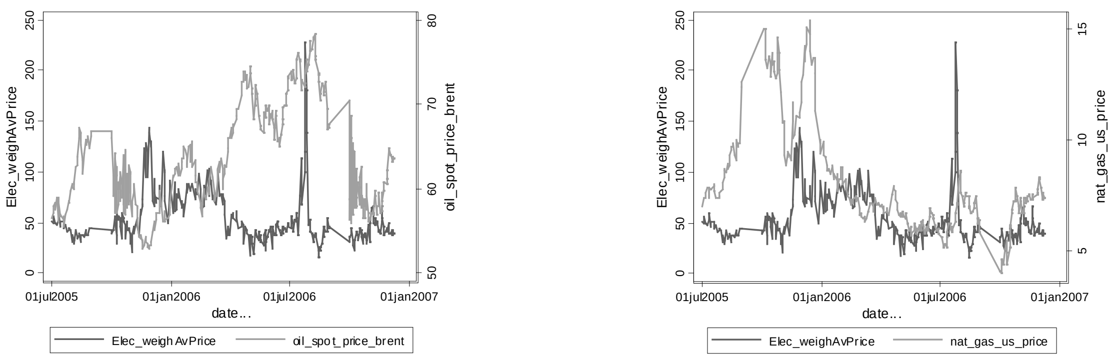

Figure 2: Commodities spot prices from 2005 to 2007

As shown by Figures, the electricity price also suffered from considerable variability. Day-head prices headed upwards during the July heat wave and displayed high volatility. The biggest spike took the baseload price to EUR 234,448/MWh on July 26th. Subsequently prices were mostly low and stable over autumn and the beginning of winter. In mid-September the eletricity spot price stood at below EURO 50/MWh.

In the following months and until the end of the phase 1, the carbon price decreased, falling to EUR 1/t in February 2007 to EUR 0,02/t in December 2007. Such a continuous drop is explained both by institutional reasons and weather conditions. Indeed, due to the excess of allowances in most of the countries after the 2006 compliance, and to the non-storability of these allowances, trades of contracts of Phase 2 on the futures market were preferred to trades on the spot market. Indeed, since October 2006, spot prices related to Phase 1 and prices of futures contracts related to Phase 2 appear to be no longer correlated. Moreover, during the same period, a high level of rain, temperatures above the seasonal average, and a drop in natural gas prices also limited the demand of allowances and reinforce the downwards trend of the carbon price.

However, although the carbon price suffered during this first phase from high volatility, the volume of the registered transactions increased over the three years: from 262 millions of tonnes in 2005, it reached 818 millions of tonnes in 2006 and finally 1,5 billions in 2007. Moreover, this price also provided a real signal to the industry and allowed installations to be prepared for the second phase of the market, where the price of carbon is already higher than the one observed during the first phase.

4 Econometrics modelisation of both markets and results

Contributions to the study of the electricity markets appear to point out the relevance of the multivariate approach to modelling the relationship between prices and volatilities of such markets. More generally, as noted by Bauwens, Laurent and Rombouts (2006), it is the most obvious application of these models in so far as they provide the appropriate framework to study issues such as: "*Is the volatility of a market leading the volatility of others markets? [or] Does a shock on a market increase the volatility on another market?*[12]". As an exemple of such contributions, Worthington, Kay-Spratley and Higgs (2005) study the transmission of the prices and price volatility in several Australian electricity spot markets (the national as well as four regional markets). They underline that using MGARCH models is useful in capturing the effect on volatility of both innovation and lagged volatility shocks and in investigating the volatility persistence and mean price transmissions in the interconnected markets.

4.1 The model

Following the literature (Bauwens, Laurent and Rombouts (2006), Silvennoinen et al. (2007) and Tsay (2005)), the traditional multivariate GARCH model is characterized as follows. Consider a stochastic vector process r_t with dimension $N \times 1$ such that $Er_t = 0$. Let F_{t-1} denote the information set generated by the observed series. We assume that r_t is conditionally heteroskedastic:

$$r_t = H_t^{1/2} \eta_t$$

given the information set F_{t-1}, where the $N \times N$ matrix $H_t = [h_{ijt}]$ is the conditional variance matrix of r_t and η_t is an iid vector error process such that $E\eta_t\eta_t' = I$.

Several constraints have to be combined to parameterise a MGARCH model. As noted by Silvennoinen and Teräsvirta (2007), it has to be flexible enough to represent the dynamics of the conditionnal variances and covariances, but also sufficiently parsimonious to allow for an easy estimation of the model and interpretation of its parameters. The positive definitivness needs also to be taken into account. Finally, several approaches or categories for constructing multivariate GARCH models are distinguished: a direct generalization of the univariate GARCH model

[12] Bauwens et al. (2006), p.79

(Bollerslev, 1990), a linear combinations of univariate GARCH models, in which the covariance matrix H_t is modelled directly (this category includes VEC and BEKK models), and nonlinear combinations of univariate GARCH models, in which one should model the conditional variances and correlations instead of straightforward modelling of the conditional covariances matrix (this category includes the Constant Conditional Correlation (CCC) model and the Dynamic Conditional Correlation (DCC) model).

The BEKK (Baba, Engle, Kraft and Kroner) parameterisation discussed by Engle and Kroner (1995) guarentees that H_t (variance-covariance matrix)is positive definite . The BEKK model is written as:

$$H_t = C^{*'}C^* + \Sigma_{k=1}^{K}\Sigma_{i=1}^{q} A_{ki}^{*'}\varepsilon_{t-i}\varepsilon_{t-i}' A_{ki}^{*} + \Sigma_{k=1}^{K}\Sigma_{j=1}^{q} G_{kj}^{*'} H_{t-j} G_{kj}^{*} \tag{1}$$

where C is a lower triangular matrix and A_{ki} and G_{kj} are $k \times k$ parameter matrices.

Since H_t is positive definite, the BEKK model allows for dynamic dependance between the volatility series. In others words, causalities in variances can be modelled. However, due to the quadratic form of the BEKK model, the parameters are not identifiable without further restriction and, as noted by Tsay (2005) and Tse and Tsui (2002), limited experience shows that many of the estimated parameters are statistically insignificant. In this regard, Bollerllev, Engle and Wooldridge (1988) suggested a multivariate GARCH model where matrices A and G are diagonal. Contrary to the full BEKK model, under this framework less parameter remain to be estimated, and no checks are needed to ensure the positive definitiviness of the covariance matrix (Pekka, Anti, 2005). Moreover, further restrictions could be applied to the full BEKK model. For example, the estimation can be done assuming a t-distribution (T-BEKK) instead of a normal distribution, which allows one to capture asymetric effects (Pekka and Antti, 2005).

Other kinds of MGARCH model's specification are developed and might be relevant in our study, in particular the Constant Conditional Correlation model (CCC model) suggested by Bollerslev (1990) and the Dynamical Conditionnal Correlation GARCH model (DCC- GARCH) proposed by Engle (2002). As quoted by Gourieroux (1997), the CCC-model assumes that all conditional correlations are time-invariant (i.e., they are constant) and conditional variances are modelled by univariate GARCH models. The model is given by Bauwens et al. (2006):

$$\begin{aligned} H_t &= D_t R D_t = (\rho_{ij}\sqrt{h_{iit}h_{hjjt}}) \\ D_t &= \mathrm{diag}(\sqrt{h_{11t}}, \sqrt{h_{22t}}, ..., \sqrt{h_{NNt}}) \\ R &= \rho_{ij}, \text{avec} \quad \rho_{iit} = 1, \forall i. \end{aligned} \tag{2}$$

where D_t is a $k \times k$ matrix with conditional standard deviations on the diagonal and R is the correlations matrix. And, $h_{iit} = \omega_i + \alpha\epsilon_{i,t-1}^2 + \beta_i h_{ii,t-1}, \forall i = 1, ..., N$.

While this model provides several relevant interpretations, in particular it allows one to easily compare correlations from a sub-period to another, the main assumption of time-invariant correlation has been rejected by several empirical studies (see Tse and Tsui, 2002). Moreover, studies on electricity markets also underline the weaknesses of this model. As an example, Pekka and Antti (2005) conclude that it is the worst candidate in parameterizing the MGARCH model in their study of the Australian electricity markets.

A possible extension of the model is the DCC model proposed by Engle (2002), which ensures time-independency of the conditional correlation matrix and also guarantees positive definitivness under simple conditions on the parameters. The dynamic correlation model differs from the CCC model only in allowing R to be time varying (Bauwens et al., 2006):

$$\begin{aligned} H_t &= D_t R_t D_t \\ D_t &= \text{diag}(\sqrt{h_{11t}}, \sqrt{h_{22t}}, ..., \sqrt{h_{NNt}}) \\ R_t &= (diagQ_t)^{-\frac{1}{2}} Q_t (diagQ_t)^{-\frac{1}{2}} \end{aligned} \tag{3}$$

where, Q_t is a $N \times N$ symetric, positive definite matrix such that:

$$Q_t = (1-\alpha-\beta)\overline{Q} + \alpha u_{t-1}u'_{t-1} + \beta Q_{t-1}.$$

where $\overline{Q}$ is the symetric, positive definite matrix $(N \times N)$ of unconditional variances-covariances. $u_t = (u_{1t}, u_{2t}, ..., u_{Nt})$is the column vector of standardized residues of N assets at date t. $\alpha$and β are non negative scalars such that $\alpha + \beta < 1$.

Overall, Engle (2002) emphasizes that DCC estimators have the flexibility of univariate GARCH models without the complexity of traditional multivariate GARCH.

Literature on electricity organised markets often used MGARCH model to further investigate the functioning of these markets. This paper extends this literature by considering the existence of possible cross-spillovers between the carbon spot market (Bluenext EUA) and the electricity spot market (Powernext Day-Ahead), as well as the impact of weather conditions and other commodities' spot prices on such a joint process. A reading of the literature leads one to conclude that modelling prices and prices volatility through multivariate GARCH models is the relevant approach.

4.2 Econometrics results

In line with our discussion above, the analysis performed are based on the estimation of a bivariate GARCH model to examine the joint process relating the daily spot prices for the Powernext Day-Ahead market and the Powernext Carbon market. However preliminary tests (i.e., tests of the stationary and the cointegration of the time series under study) as well as several estimations (i.e., definition of the conditional expected returns equation) need to be done before turning to the estimation of a multivariate GARCH model.

4.2.1 Preliminary tests

In order to define the best way to investigate the dynamic interactions between the two spot prices, one should first check the stationnarity and the cointegration of these prices. Indeed, if both prices are stationnary, we could directly work on prices (i.e., VAR in levels). On the contrary, if they are not stationnary, that means that there is definite positive or negative trend over time. Taking the first difference then allows to remove this trend in the series. Moreover, if the two spot prices are also cointegrated, one could theme define a cointegrated VAR to study interactions between variables, rather than a simple VAR in difference.
The stationary of the variables is investigated by means of the augmented Dickey Fuller test (ADF), which uses the autoregressive model specified below:

$$\delta y_t = \alpha y_{t-1} + \delta_0 + \delta_1 t + \Sigma_{k=1} p - 1 \beta \Delta y_{t-k} + \epsilon_t$$

where,y_t is an element of the p-dimensional vector Y_t of the time series under study and ϵ_t is a white noise process. The null hypothesis (H_0) of non-stationary (called unit root) is given by $\alpha = 0$. The test for a unit root is based on the t-stat on the coefficient of the lagged dependent variable, y_{t-1}. If this is greater than the critical value, then the null hypothesis of a unit root is rejected, and the variable is taken to be stationary. According to table 1, for the case of the carbon variable the ADF t-stat is lower than the critical value at 1%, 5% and 10%, and thus one cannot reject the null hypothesis implying that the price of carbon is not stationary. However, with regard to the electricity variable, the null hypothesis is rejected at all standard significance levels, and thus the price of electricity can be considered to be stationary.

In terms of investigating possible co-integration between the carbon and electricity prices, the Johansen approach proposes to maximize the likelihood function over a subset of parameters, treating the other parameters as known. Defining r as the number of cointegrating vectors, Johansen suggests a sequential test (trace test) to estimate their possible existence. Table 2 shows that the first null hypothesis of "no cointegrating vectors" is rejected for by standard confidence levels. The next hypothesis of "at most one cointegrating vector" is similarly rejected for critical value at 5% and 10% significance levels. Thus the cointegration tests seems to suggest that there is at least one cointegrating vector between our two price series.

Our finding with regard the existence of vector(s) of cointegration appear to point out the limited efficiency of using a methodology based on VAR-models in levels to study the dynamic interactions between the two spot prices. Two main ways could be developed in order to perform our estimations. First, we could specify VAR-models in differences, and thus work on the returns of the spot prices, i.e., focus on the differences of the log of these returns instead of directly working on the spot prices. Second, we could specify a cointegrated VAR. We investigate both of these two methods below.

4.2.2 Definition and estimation of the conditional expected return equation

VAR-models in differences do not allow to isolate any possible long-run relationship that might exist between variables. Define R_t^c and R_t^e as the log returns at period t related to the spot prices of respectively carbon and electricity. To study the existence of such a long run relationship between the two variables, we first ran the following regression:

$$R_t^c = \alpha + \beta R_t^e + \epsilon_t \tag{4}$$

Results (table 3) show that an increase of the carbon price leads to an increase of the electricity price (i.e., $\alpha > 0$ and $\beta > 0$). In the long term, however, carbon and electricity prices seem to be related .

Let us now turn to the VAR-models. Such an approach allows one to define the equation that accommodates each market's own returns to the return of the other market lagged one period. The VAR-model is defined as follows, and the estimated coefficients are presented in table 4.

$$R_t^c = \alpha + a_{11} R_{t-1}^c + a_{12} R_{t-1}^e + \epsilon_t \tag{5}$$

$$R_t^e = \alpha + a_{21} R_{t-1}^c + a_{22} R_t^e - 1 + \epsilon_t \tag{6}$$

The two markets exhibit a significant own mean spillover from their own lagged return. Regarding the carbon market, the mean spillover is positive and thus an increase of EUR 1/t of CO2 in the return related to the spot prices will cause an increase of EUR 0,23/t of CO2 in the return over the next day. On the contrary, on the electricity spot market, the mean spillover is negative, and thus an increase of EUR 1/MWh in the return will lead to a decrease of EUR 0,29/MWh in the returns over the next day. Indeed, the Granger tests exhibit a significant causality between each dependent variable and its lagged value (see table 5). However, there are no significant lagged mean spillovers from one spot market to another. Such a result indicates that in the short run on average changes in returns in the electricity spot market are not associated with changes in returns in the carbon spot market and vice versa.

For a more realistic modelling of the market one should arguably also take into account the potential impact of weather variations on the two markets. The estimations below extend the VAR-model previously defined by including as exogenous variables temperature indices of France, Belgium, Germany, Italy, Netherlands, Portugal, Spain and Switzerland, as well as rainfall in

France. Tables 6 and 7 display the estimated coefficients of this exercise. Here again the two markets exhibit a significant own mean spillover from their own lagged return - an increase of EUR 1/t of CO2 or of EUR 1/MWh in returns will lead to an increase of respectively EUR 0,21/t of CO2 and EUR 0,54/MWh in returns over the next day-, but no significant cross effects between the two markets. Regarding the impact of climate variables, neither rainfall and temperature in France nor temperature in others countries have an influence on carbon returns. However, the estimation of the electricity returns at date t, exhibits a significant but low impact of the variable HDD_s. In others words, warmer conditions in Spain lead to an increase of EUR 0,05/MWh of the electricity returns on the French spot market.

Our general results are robust to the inclusion of other commodities' spot markets (i.e., oil and natural gas market) into the VAR-model (see tables 8 to 11). The estimations ran underline a positive own mean spillover on the carbon spot market (EUR +0,21/t of CO2 over the next day) and a negative one on the electricity spot market (EUR -0,34/MWh over the next day), but no significant cross effects between these two markets is apparent. Regarding the other commodities' markets, the results show a negative own mean spillover on the oil market (USD -0,19/barrels over the next day) but no such effect on the natural gas market. Nevertheless, a significant cross mean spillover effect appears with the oil market when estimating the natural gas returns. In others words, on average short-run returns changes on the oil spot market are associated with returns changes over the next day on the natural gas spot market (USD -0,23/mbtu). Finally, temperature as well as rain do not have any influence on carbon and gas returns, while, as previously mentioned, warmer temperature in Spain leads to higher expected returns on the electricity market, and a similar effect is found with regard to warmer temperature in France, Germany (Belgium and Portugal) on the oil market. However such impacts are very low, they range from USD -0,005/barrels to USD +0,05/barrels.

As previously mentioned, another way to investigate the dynamic interaction between carbon and electricity spot markets is to perform a cointegrated VAR model, using the errors terms of the previous VAR in differences models as an additional variable. The cointegrated VAR, i.e., the so called error correction mechanism model, allows one to investigate the changes in the variables on lags (i.e. returns), as well as the deviations from the long term relation between these variables. The ECM model is written as follows:

$$\Delta R_t^c = \alpha_c + A_{11}\Delta R_{t-1}^c + A_{12}\Delta R_{t-1}^e + \delta_1\epsilon_{t-1} \tag{7}$$

$$\Delta R_t^e = \alpha_e + A_{21}\Delta R_{t-1}^c + A_{22}\Delta R_{t-1}^e + \delta_2\epsilon_{t-1} \tag{8}$$

Coefficients estimations are given in Tables 12 and 13. Results first of all show that there is no short run relationship between carbon and electricity returns (i.e., A_{12} and A_{21} are not significant and thus equal to zero). They also point out the existence of a disequilibrium between the two spot prices. As $\epsilon_t > 0$, it seems that carbon prices are too high relative to electricity prices in equilibrium. In such a case, two possibilities may arise to re-establish the long run relationship: either the carbon price decreases or the electricity price increases. In our case, as δ_2 is significant, while δ_1 equals to zero, it seems that electricity is doing the adjustment rather that carbon.

Importantly, however, when including weather proxies as exogenous variables into the ECM (see tables 14 and 15), δ_1 becomes significant and δ_2 zero. Given that now, in taking weather conditions into account, there is still no short run relationship between carbon and electricity returns, it would appear that in the long run it is carbon rather than electricity that is doing the adjustment to be in equilibrium.

4.2.3 Estimations of bivariate GARCH

We next employ a bivariate GARCH model to study the joint processes related to daily rates of returns on both the electricity and carbon markets. The conditional variance-covariance equations described in the previous section capture the volatility and the cross-volatility spillovers among the two markets studied. Tables 10 to 12 present the estimated coefficients for the variance-covariance matrix of equations regarding three possible parameterisations of our bivariate GARCH model: full BEKK, CCC and DCC. Coefficients of the variance-covariance equations quantify the effects of the lagged own and cross innovations and of the own and cross-volatility spillovers to the individual returns for both electricity and carbon markets, indicating the presence of ARCH or GARCH effects.

In the BEKK models the parameters a_{11} and a_{22} also indicate the presence of own-innovation spillovers effects in both markets and these effects range from 0.0106 to 0.907 on the carbon spot market, and from 0.148 to 0.335 on the electricity market. Regarding the different models, all of them exhibit significant ARCH effects. Indeed, both in the CCC and DCC models, the ARCH parameters α_1 and α_2 are significant. Own volatility spillovers (i.e., g_{11} and g_{22}) are significant on both markets in the BEKK's estimations. This means that past volatility shocks on a market has a significant effect on the future volatility of this market. Also, the GARCH parameters are significant in the CCC and DCC models. GARCH effects seem to appear in the two markets. Nevertheless, according to the BEKK estimations, there is no cross-volatility spillovers between the two markets.

However, none of the models used exhibit any cross-innovation effects between carbon and electricity markets. Regarding the BEKK model's estimations, there might be a possible cross-innovation effect from the electricity market to the carbon market, meaning that past innovations in the electricity market exert an influence of the carbon market, while the contrary is not significant. Such a result would be consistent with those of the ECM model. One may want to note, however, that such an effect is only very weakly statistically significant.

5 Conclusion and perspectives

This paper has investigated the existence of possible interactions between carbon and electricity spot markets on the French trading platforms over the period June 2005 to July 2006. The sample under study is a part of the phase 1 of the EU ETS, which covers the period from June 2005 to December 2007. One may want to note in this regard that our sample leave apart the period in which the price continuously fell mainly because of institutional reasons. Indeed, from October 2006 actors on the market arguably completely lost interest during the first phase of the spot market, and the price of carbon was not able to provide any incentives. However, while the sample under study might perceived to be limited, it does represent a period during which the market was able to send a "price signal" to CO2 actors, where there were considerable variations in climate, as well as market and institutional shocks.

Our unit roots tests confirm that Powernext electricity spot prices are stationnary, as has been found for others trading plateforms (Worthington et al. (2005), Pekka, Antti (2005), De Vanis, Walls (1999), Byström (2003)), while Powernext carbon spot prices are not stationary. The coefficients of the conditional mean returns equation estimated through VAR always indicate that both markets are integrated, suggesting that electricity and carbon returns could be forecasted using lagged returns information from each market itself. However, since no significant cross effects are highlighted by the results, it is not possible to forecast returns on a specific market using information from the other market. Moreover, results from the ECM model emphasize a lack of a short run relationship between the two markets, as well as the existence of a disequilibrium between the two spot prices in the long run. Taking other commodities' markets into account, results also point out the lack of mean cross effect between carbon market, and oil or natural gas markets. Finally, our paper highlights the limited impact of climate variations on both electricity and carbon returns. Nevertheless, unsurprisingly, we found the existence of both own and cross effects between several commodities market (i.e., gas and oil).

A range of bivariate GARCH models are used to investigate the magnitude of own and cross volatility spillovers between the carbon and the electricity returns. Own volatility spillovers are significant, indicating the presence of ARCH effects. Regarding estimations of the CCC and DCC models, GARCH parameters are also significant, while according to the BEKK's model, there are no significant cross volatility spillovers. Such results seem to indicate the presence of GARCH effects, and thus the inefficiency of both markets, although this is not clear-cut. However, according to the BEKK model, the electricity spot market and the carbon spot market are not integrated, and shocks or innovations in a particular market do not exert any influence on the volatility of returns. Thus, the conclusions regarding integration clearly depend on the choice model and hence the differences in underlying assumptions between these.

One other main conclusion highlighted by our results is the limited or the lack of influence of weather variables on electricity and carbon returns. Regarding rain data in France, such lack of impact on carbon returns is mainly explained by the minor role of hydropower in the energy mix of the country. Indeed, in France, 80% of the electricity production is due to nuclear energy, and the pluviometry of the country thus mostly influences the production through the cooling of nuclear generators. More surprising is the lack of relationship between temperature in France and electricity returns, although there is a significant relation between the temperature in France and the quantity of electricity traded on Powernext (see table 19). However, results also underline a positive relationship between warmer conditions in Spain and electricity returns in France. As the electricity production in Spain is largely dependant on hydropower, in previous years the country had to replace the lack of hydroelectricity due to a low level of rainfall by thermal or fuel power and by imports. Thus an increase of power demand due to warmer temperature (i.e., air conditioning) may had led to an increase of electricity imports from France (and elsewhere), and thus to an increase in the electricity returns on Powernext market.

As previously noted, our findings underline the likelihood that there is no returns or shocks diffusion between the French carbon and electricity markets, as well as other commodities' spot markets. Such a result may not be surprising given that the carbon and the electricity markets studied are national markets, while Brent oil and Henry Hub natural gas are traded worldwide. But, taking into account such prices into our analysis allowed for a arguably better estimation of the residual in the VAR and ECM models, and thus of the bivariate GARCH.

Finally, all of our results have to be digested with some caution, since the return and volatility interrelationships between these separate markets might be understated by mis-specification in the data. Nevertheless, all of the estimations performed in this paper emphasize the impact of the rules that control the functioning of the EU market. Since the first phase was an experimental phase of the market, it was perhaps not such a bad thing that carbon market and others commodities market were not interconnected. Regarding the instability of the carbon market during this first phase, such a disconnection between markets that should have interacted with it have clearly prevented other commodities' market to suffer from unexpected shocks that are not linked to their own functioning. However, if neither climate variations nor commodities returns can explain the lack of interrelationship between electricity and carbon markets, it thus seems that the absence of the possibility of arbitrage during the first phase on the carbon market enabled the interaction with electricity market as others commodities market do. In others words, if carbon market should be considered as a commodity market, the rules enforce during the first phase do not allow any speculative behaviours. This limits the liquidity of the market but also reduces the efficiency of the carbon price to act as an incentive to limit CO2 emissions. One may contentiously hope that the second phase will provide a completely different role for the carbon market by combining environmental performance to trading opportunities in order to enhance both its liquidity and its maturity.

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Annex

- Tests of stationnarity and cointegration

ADF test for unit root variable	**ADF t-statistic**	**Number of lags**	
Carbon	-2.384796	1	
Electricity	-4.405369	1	
ADF test for unit root variable	**90%**	**95%**	**99%**
Critical value	-3.446	-2.842	-2.573

Table 1: Augmented Dickey Fuller Test

H_0	**Trace statistic**	**Eigen statistic**	**Crit. Value 90%**	**Crit. Value 95%**	**Crit. Value 99%**
r¡=0	24.912	19.405	12.297	14.264	18.520
r¡=1	5.508	5.508	2.705	3.841	6.635

Table 2: Johansen MLE estimations

- Long term relationship between carbon and electricity returns

The estimated model is:

$$R_t^c = \alpha + \beta R_t^e + \epsilon_t$$

Dependent Variable	**Carbon**		
Variable	Coefficient	t-statistic	t-probability
α	2.457842	17.158938	0.000000
β	0.150639	4.258736	0.000028

Table 3: Cointegrating relationship in level between carbon and electricity spot returns

- VAR models in difference

The estimated model is:

$$R_t^c = \alpha + a_{11}R_{t-1}^c + a_{12}R_{t-1}^e + \epsilon_t$$

$$R_t^e = \alpha + a_{21}R_{t-1}^c + a_{22}R_t^e - 1 + \epsilon_t$$

Dependent Variable	**Carbon**		
Variable	Coefficient	t-statistic	t-probability
Carbon lag1 ($a_1 1$)	0.232804	3.909581	0.000117
elect lag1 ($a_1 2$)	0.001226	0.070609	0.943762
constant	-0.001105	-0.358529	0.720231
Dependent Variable	**Electricity**		
Variable	Coefficient	t-statistic	t-probability
Carbon lag1 ($a_2 1$)	0.103118	0.480601	0.631194
elect lag1 ($a_2 2$)	-0.292568	-4.677589	0.000005
constant	0.000314	0.028240	0.977492

Table 4: VAR model between carbon and electricity returns

- Granger causality tests

Dependent Variable	**Carbon**	
Variable	F-value	Probability
Carbon	15.284820	0.000117
Electricity	0.004986	0.943762
Dependent Variable	**Electricity**	
Variable	F-value	Probability
Carbon	0.230977	0.631194
Electricity	21.879838	0.000005

Table 5: Granger causality tests

- VAR model in difference with weather variables as exogenous variables

The estimated model is:

$$R_t^c = \alpha + a_{11}R_{t-1}^c + a_{12}R_{t-1}^e + \pi_f nrain_{f,t} + \Sigma_i h_i HDD_{i,t} + \Sigma_i c_i CDD_{i,t} + \epsilon_t$$

pour i=f, b, g, i, n, p, s, ch.

Dependent Variable	**Carbon**		
Variable	Coefficient	t-statistic	t-probability
R_{t-1}^c	0.214281	3.494350	0.000562
R_{t-1}^e	-0.003819	-0.212342	0.832013
$nrain_f$	-0.005492	-1.282608	0.200817
HDD_f	-0.001179	-0.185035	0.853351
HDD_b	0.002543	0.900584	0.368677
HDD_g	0.000751	0.116751	0.907151
HDD_i	0.000124	0.056359	0.955101
HDD_n	0.000988	0.304341	0.761121
HDD_p	-0.001068	-0.237334	0.812592
HDD_s	-0.000115	-0.013816	0.988988
HDD_{ch}	0.000281	0.075897	0.939561
CDD_f	-0.005239	-1.395486	0.164108
CDD_b	0.003804	1.300074	0.194773
CDD_g	-0.000084	-0.038907	0.968996
CDD_i	-0.002737	-0.764818	0.445101
CDD_n	0.003076	0.750327	0.453763
CDD_p	-0.001803	-0.370129	0.711600
CDD_s	0.000781	0.305727	0.760067
CDD_{ch}	0.003518	1.622114	0.106039
constant	-0.019425	-1.374986	0.170367

Table 6: VAR model between carbon and electricity returns with weather variables as exogenous variables

The estimated model is:

$$R_t^e = \alpha + a_{21} R_{t-1}^c + a_{22} R_{t-1}^e + \pi_f nrain_{f,t} + \Sigma_i h_i HDD_{i,t} + \Sigma_i c_i CDD_{i,t} + \epsilon_t$$

pour i=f, b, g, i, n, p, s, ch.

Dependent Variable	**Electricity**		
Variable	Coefficient	t-statistic	t-probability
R_{t-1}^c	0.115813	0.538988	0.590375
R_{t-1}^e	-0.349906	-5.552244	0.000000
$nrain_f$	-0.015921	-1.061096	0.289670
HDD_f	-0.012672	-0.567518	0.570872
HDD_b	0.003571	0.360944	0.718446
HDD_g	0.008306	0.368605	0.712734
HDD_i	0.006215	0.803988	0.422168
HDD_n	-0.002005	-0.176245	0.860244
HDD_p	0.001436	0.091052	0.927525
HDD_s	0.057462	1.978698	0.048947
HDD_{ch}	0.013114	1.011276	0.312862
CDD_f	0.010231	0.777721	0.437469
CDD_b	-0.005905	-0.575846	0.565237
CDD_g	-0.010452	-1.389855	0.165809
CDD_i	-0.009396	-0.749280	0.454393
CDD_n	-0.003746	-0.260775	0.794481
CDD_p	-0.007447	-0.436321	0.662981
CDD_s	0.004707	0.525924	0.599407
CDD_{ch}	0.007493 0	.986094	0.325041
constant	-0.070772	-1.429655	0.154065

Table 7: VAR model between carbon and electricity returns with weather variables as exogenous variables

- VAR models in différence between eletricity, carbon, natural gas and oil returns with weather variables as exogenous variables

The estimated model is:

$$R_t^c = \alpha + a_{11} R_{t-1}^c + a_{12} R_{t-1}^e + a_{13} R_{t-1}^{ng} + a_{14} R_{t-1}^o + \pi_f nrain_{f,t} + \Sigma_i h_i HDD_{i,t} + \Sigma_i c_i CDD_{i,t} + \epsilon_t$$

where, R_t^o et $R_t^{ng}$are oil and gas returns andt i=f, b, g, i, n, p, s, ch.

Dependent Variable	**Carbon**		
Variable	Coefficient	t-statistic	t-probability
R_{t-1}^c	0.215549	3.490593	0.000570
R_{t-1}^e	-0.003706	-0.205226 0.837564	
R_{t-1}^{ng}	-0.021738	-0.306598 0.759407	
R_{t-1}^o	-0.005377	-0.034749 0.972308	
$nrain_f$	-0.005569	-1.292586 0.197357	
HDD_f	-0.001356	-0.211086 0.832993	
HDD_b	0.002583	0.908929 0.364270	
HDD_g	0.000896	0.138229 0.890172	
HDD_i	0.000199	0.089163 0.929024	
HDD_n	0.000943	0.288832 0.772951	
HDD_p	-0.000984	-0.217279 0.828170	
HDD_s	-0.000016	-0.001897 0.998488	
HDD_{ch}	0.000263	0.070735 0.943666	
CDD_f	-0.005188	-1.372403 0.171178	
CDD_b	0.003784	1.287570 0.199096	
CDD_g	-0.000097	-0.044769 0.964327	
CDD_i	-0.002706	-0.750203 0.453843	
CDD_n	0.003248	0.780512 0.435834	
CDD_p	-0.001961	-0.398517 0.690592	
CDD_s	0.000791	0.308530 0.757938	
CDD_{ch}	0.003487	1.600106 0.110848	
constant	-0.019699	-1.386014 0.166987	

Table 8: VAR model between carbon, electricity, oil and natural gas returns with weather variables as exogenous variables

The estimated model is:

$$R^e_t = \alpha + a_{21}R^c_{t-1} + a_{22}R^e_{t-1} + a_{23}R^{ng}_{t-1} + a_{24}R^o_{t-1} + \pi_f nrain_{f,t} + \Sigma_i h_i HDD_{i,t} + \Sigma_i c_i CDD_{i,t} + \epsilon_t$$

where, R^o_t et $R^{ng}_t$are oil and gas returns andt i=f, b, g, i, n, p, s, ch.

Dependent Variable	**Electricity**		
Variable	Coefficient	t-statistic	t-probability
R^c_{t-1}	0.146028	0.679404	0.497515
R^e_{t-1}	-0.348122	-5.538160	0.000000
$R^{ng}c_{t-1}$	-0.406892	-1.648777	0.100459
R^o_{t-1} lag1	-0.391750	-0.727387	0.467675
$nrain_f$	-0.017724	-1.181959	0.238354
HDD_f	-0.016144	-0.722274	0.470807
HDD_b	0.004661	0.471269	0.637863
HDD_g	0.010655	0.472520	0.636971
HDD_i	0.007511	0.967987	0.333994
HDD_n	-0.002819	-0.248197	0.804187
HDD_p	0.002778	0.176198	0.860282
HDD_s	0.060714	2.087805	0.037836
HDD_{ch}	0.012801	0.989785	0.323244
CDD_f	0.011697	0.889080	0.374821
CDD_b	-0.006165	-0.602645	0.547295
CDD_g	-0.010863	-1.447233	0.149094
CDD_i	-0.009347	-0.744551	0.457248
CDD_n	0.000172	0.011890	0.990523
CDD_p	-0.010962	-0.640060	0.522725
CDD_s	0.004905	0.549494	0.583161
CDD_{ch}	0.006982	0.920389	0.358264
constant	-0.076827	-1.552995	0.121700

Table 9: VAR model between carbon, electricity, oil and natural gas returns with weather variables as exogenous variables

The estimated model is:

$$R_t^{ng} = \alpha + a_{31}R_{t-1}^c + a_{32}R_{t-1}^e + a_{33}R_{t-1}^{ng} + a_{34}R_{t-1}^o + \pi_f nrain_{f,t} + \Sigma_i h_i HDD_{i,t} + \Sigma_i c_i CDD_{i,t} + \epsilon_t$$

where, R_t^o et $R_t^{ng}$are oil and gas returns andt i=f, b, g, i, n, p, s, ch.

Dependent Variable	**Henry Hub natural gas**		
Variable	Coefficient	t-statistic	t-probability
R_{t-1}^c	0.071762	1.280544	0.201550
R_{t-1}^e	0.002110	0.128738	0.897669
R_{t-1}^{ng}	0.019650	0.305381	0.760332
R_{t-1}^o	-0.235320	-1.675804	0.095037
$nrain_f$	-0.004831	-1.235677	0.217748
HDD_f	-0.000243	-0.041756	0.966727
HDD_b	0.000044	0.016973	0.986472
HDD_g	-0.006813	-1.158767	0.247666
HDD_i	0.002349	1.161226	0.246667
HDD_n	-0.000518	-0.174808	0.861373
HDD_p	0.004598	1.118396	0.264480
HDD_s	0.006453	0.851101	0.395535
HDD_{ch}	0.003353	0.994507	0.320945
CDD_f	0.000674	0.196460	0.844411
CDD_b	0.001522	0.570479	0.568869
CDD_g	-0.001495	-0.763761	0.445735
CDD_i	0.001812	0.553736	0.580259
CDD_n	0.004217	1.116771	0.265173
CDD_p	-0.005257	-1.177367	0.240178
CDD_s	-0.003040	-1.306257	0.192675
CDD_{ch}	-0.002174	-1.099216	0.272740
constant	-0.002720	-0.210880	0.833154

Table 10: VAR model between carbon, electricity, oil and natural gas returns with weather variables as exogenous variables

The estimated model is:

$$R_t^p = \alpha + a_{41}R_{t-1}^c + a_{42}R_{t-1}^e + a_{43}R_{t-1}^{ng} + a_{44}R_{t-1}^o + \pi_f nrain_{f,t} + \Sigma_i h_i HDD_{i,t} + \Sigma_i c_i CDD_{i,t} + \epsilon_t$$

where, R_t^o et $R_t^{ng}$are oil and gas returns andt i=f, b, g, i, n, p, s, ch.

Dependent Variable	**Brent oil**		
Variable	Coefficient	t-statistic	t-probability
R_{t-1}^c	0.002226	0.089969	0.928384
R_{t-1}^e	0.001828	0.252555	0.800822
R_{t-1}^{ng}	0.041738	1.468927	0.143120
R_{t-1}^o	-0.192762	-3.108624	0.002099
$nrain_f$	0.000552	0.319447	0.749656
HDD_f	0.005599	2.175687	0.030523
HDD_b	0.002339	2.054144	0.041010
HDD_g	-0.005363	-2.065786	0.039888
HDD_i	-0.000377	-0.421851	0.673499
HDD_n	-0.000735	-0.562196	0.574490
HDD_p	-0.004523	-2.491253	0.013384
HDD_s	0.004488	1.340399	0.181342
HDD_{ch}	-0.000180	-0.121148	0.903672
CDD_f	0.001111	0.733424	0.463992
CDD_b	-0.000373	-0.317027	0.751490
CDD_g	0.000556	0.643403	0.520557
CDD_i	-0.000636	-0.440341	0.660074
CDD_n	0.001214	0.728048	0.467271
CDD_p	-0.001188	-0.602485	0.547402
CDD_s	-0.000339	-0.330122	0.741586
CDD_{ch}	0.000513	0.586989	0.557745
constant	-0.002158	-0.378844	0.705128

Table 11: VAR model between carbon, electricity, oil and natural gas returns with weather variables as exogenous variables

- ECM Model

The estimated model is:

$$\Delta R_t^c = \alpha_c + A_{11}\Delta R_{t-1}^c + A_{12}\Delta R_{t-1}^e + \delta_1\epsilon_{t-1}$$

Dependent Variable	**Carbon**		
Variable	Coefficient	t-statistic	t-probability
ΔR_{t-1}^c	0.234243	3.922677	0.000112
ΔR_{t-1}^e	-0.002994	-0.164628	0.869362
ϵ_{t-1}	-0.002698	-0.872353	0.383806
constant (α_c)	-0.018761	-0.920177	0.358317

Table 12: ECM estimations

The estimated model is:

$$\Delta R_t^e = \alpha_e + A_{21}\Delta R_{t-1}^c + A_{22}\Delta R_{t-1}^e + \delta_2\epsilon_{t-1}$$

Dependent Variable	**Electricity**		
Variable	Coefficient	t-statistic	t-probability
ΔR_{t-1}^c	0.076853	0.364098	0.716075
ΔR_{t-1}^e	-0.229713	-3.573902	0.000418
ϵ_{t-1}	0.036644	3.351572	0.000921
constant (α_e) 0.238859 3.314320 0.001047			

Table 13: ECM estimations

- ECM model with weather variables

The estimated model is:

$$\Delta R_t^c = \alpha_c + A_{11}\Delta R_{t-1}^c + A_{12}\Delta R_{t-1}^e + \delta_1\epsilon_{t-1} + pi_f nrain_{f,t} + \Sigma_i h_i HDD_{i,t} + \Sigma_i c_i CDD_{i,t}$$

with i=f, b, g, i, n, p, s, ch.

Dependent Variable	**Carbon**		
Variable	Coefficient	t-statistic	t-probability
ΔR_{t-1}^c	0.173202	2.738157	0.006626
ΔR_{t-1}^e	-0.002766	-0.154836	0.877077
ϵ_{t-1}	0.078830	2.374547	0.018332
dummy cret	-0.034321	-0.657132	0.511705
$nrain_f$	-0.005706	-1.338825	0.181854
HDD_f	-0.003525	-0.550557	0.582433
HDD_b	0.001890	0.671285	0.502664
HDD_g	0.001966	0.307011	0.759092
HDD_i	0.000107	0.048780	0.961134
HDD_n	0.001183	0.366603	0.714228
HDD_p	0.000268	0.059413	0.952671
HDD_s	-0.002827	-0.340327	0.733898
HDD_{ch}	0.000932	0.252831	0.800608
CDD_f	-0.005275	-1.414711	0.158408
CDD_b	0.002899	0.989654	0.323308
CDD_g	0.000435	0.203102	0.839222
CDD_i	-0.003221	-0.905240	0.366217
CDD_n	0.002392	0.582334	0.560871
CDD_p	-0.000696	-0.142794	0.886569
CDD_s	0.000994	0.391638	0.695662
CDD_{ch}	0.003151	1.460004	0.145555
constant	-0.013035	-0.912619	0.362329

Table 14: ECM estimations with weather variables

The estimated model is:

$$\Delta R_t^e = \alpha_e + A_{21}\Delta R_{t-1}^c + A_{22}\Delta R_{t-1}^e + \delta_2\epsilon_{t-1} + pi_f nrain_{f,t} + \Sigma_i h_i HDD_{i,t} + \Sigma_i c_i CDD_{i,t}$$

with i=f, b, g, i, n, p, s, ch.

Dependent Variable	**Electricity**		
Variable	Coefficient	t-statistic	t-probability
ΔR_{t-1}^c	0.147811	0.669008	0.504113
ΔR_{t-1}^e	-0.353780	-5.670693	0.000000
ϵ_{t-1}	-0.075565	-0.651665	0.515221
dummy cret	-0.458598	-2.513834	0.012577
$nrain_f$	-0.018628	-1.251419	0.211961
HDD_f	-0.009893	-0.442341	0.658628
HDD_b	0.003504	0.356243	0.721962
HDD_g	0.006974	0.311743	0.755498
HDD_i	0.006253	0.817614	0.414362
HDD_n	-0.003018	-0.267828	0.789054
HDD_p	0.000378	0.024035	0.980844
HDD_s	0.060217	2.075675	0.038955
HDD_{ch}	0.011684	0.907653	0.364943
CDD_f	0.011543	0.886198	0.376369
CDD_b	-0.005933	-0.579862	0.562534
CDD_g	-0.009851	-1.315935	0.189411
CDD_i	-0.009707	-0.781045	0.435521
CDD_n	0.001185	0.082552	0.934274
CDD_p	-0.011386	-0.669173	0.504007
CDD_s	0.003992	0.450386	0.652826
CDD_{ch}	0.008099	1.074217	0.283769
constant	-0.068742	-1.377877	0.169483

Table 15: ECM estimations with weather variables

- Bivariate GARCH models

BEKK model

The estimated model is:

$$H_t = C^{*'} C^* + \Sigma_{k=1}^{2} \Sigma_{i=1}^{2} A_{ki}^{*'} \varepsilon_{t-i} \varepsilon_{t-i}' A_{ki}^* + \Sigma_{k=1}^{2} \Sigma_{j=1}^{2} G_{kj}^{*'} H_{t-j} G_{kj}^*$$

Coefficient	Coefficient	t-statistic	t-probability
ω_{11}	0.012404	5.976141	0.000000
ω_{12}	0.013167	0.654153	0.513594
ω_{22}	0.024107	1.561290	0.119676
a_{11}	0.902227	6.978659	0.000000
a_{12}	0.170062	0.798225	0.425471
a_{21}	-0.052327	-2.634401	0.008936
a_{22}	0.335440	5.812263	0.000000
g_{11}	0.513341	5.612157	0.000000
g_{12}	-0.191037	-1.309161	0.191640
g_{21}	0.006933	0.586260	0.558211
g_{22}	0.939849	61.073762	0.000000

Table 16: BEKK model's estimations

CCC model

The estimated model is:

$$\begin{aligned} H_t &= D_t R D_t = (\rho_{ij}\sqrt{h_{iit}h_{hjjt}}) \\ D_t &= \text{diag}(\sqrt{h_{11t}}, \sqrt{h_{22t}}) \\ R &= \rho_{ij}, \text{avec} \quad \rho_{iit} = 1, \forall i, j = 1, 2. \end{aligned}$$

Coefficient	Coefficient	t-statistic	t-probability
ω_1	0.013454	263.691488	0.001294
α_1	0.010691	0.051720	0.000723
β_1	0.022105	0.203466	0.007480
ω_2	0.823766	1254.005459	0.300238
α_2	0.335525	7.958680	0.000485
β_2	0.573554	14.021427	0.000000
ρ	0.944524	16.078167	0.292687

Table 17: CCC model's estimations

DCC model

The estimated model is:

$$\begin{aligned} H_t &= D_t R_t D_t \\ D_t &= \text{diag}(\sqrt{h_{11t}}, \sqrt{h_{22t}}) \\ R_t &= (diagQ_t)^{-\frac{1}{2}} Q_t (diagQ_t)^{-\frac{1}{2}} \end{aligned}$$

Coefficient	Coefficient	t-statistic	t-probability
ω_1	0.000166	3.251809	0.001297
α_1	0.707145	3.417274	0.000733
β_1	0.292853	2.695553	0.007482
ω_2	0.000682	1.042311	0.298229
α_2	0.148950	3.533903	0.000484
β_2	0.851048	20.859998	0.000000
α	0.000002	0.000256	0.999796
β	0.000002	0.000001	0.999999

Table 18: DCC model's estimations

- Régression (OLS) between electrcity quantity and weather variables The estimated model is:$Q_t = i_f nrain_{f,t} + \Sigma_i h_i HDD_{i,t} + \Sigma_i c_i CDD_{i,t}$, with i=f, b, g, i, n, p, s, ch.

Dependent Variable	**Electricity:**	**daily volume of transactions**	
Variable	Coefficient	t-statistic	t-probability
$nrain_f$	-2935.255499	-2.155764	0.032042
HDD_f	389.386812	0.193101	0.847035
HDD_b	1942.049008	2.229504	0.026655
HDD_g	5437.149330	2.703506	0.007324
HDD_i	714.941683	1.016220	0.310492
HDD_n	3786.612639	3.735902	0.000231
HDD_p	-377.166000	-0.269297	0.787920
HDD_s	-4287.349613	-1.629746	0.104395
HDD_{ch}	-5409.848947	-4.896817	0.000002
CDD_f	3903.772103	3.241572	0.001348
CDD_b	-503.542387	-0.533930	0.593857
CDD_g	1298.868502	1.881441	0.061056
CDD_i	-2193.597799	-1.930246	0.054690
CDD_n	6175.568770	4.739864	0.000004
CDD_p	-6927.810023	-4.473434	0.000012
CDD_s	4304.784334	6.123840	0.000000
CDD_{ch}	4934.581495	8.382901	0.000000

Table 19: Impact of weather on the quantity of electricity traded